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Ensemble Learning for BOF Steelmaking End-point Temperature Prediction: A Comparative Analysis with Neural Network

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Introduction

Basic oxygen furnace (BOF) process is a globally technique, which contributes over 70% in the steelmaking industry[1]. Iron and steel industry accounts for approximately 7.2% of the global carbon emissions. The steel industry is under pressure due to an increasing emphasis on industrial decarbonization policies aimed at limiting global warming[2].

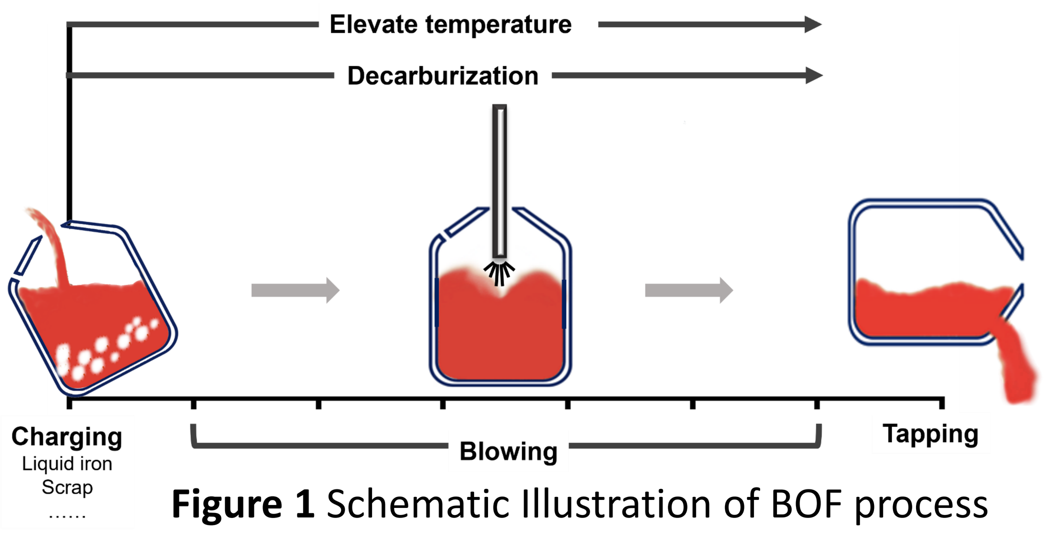

Figure 1 Schematic Illustration of BOF process

Machine learning became a research hotspot to optimize the BOF process recent years[3]. Ensemble learning is machine learning approach that combines multiple models to improve the accuracy, robustness, and reliability of predictions[4]. In this research, five machine learning models were developed to predict end-point temperature of BOF process. A comprehensive comparative analysis of all these models was performed to evaluate their effectiveness.

Data Preprocessing and modelling

In this work, a dataset of 39591 heats was gathered from a Chinese steel company, spanning from April 2021 to March 2022 and encompassing 259 steel grades.

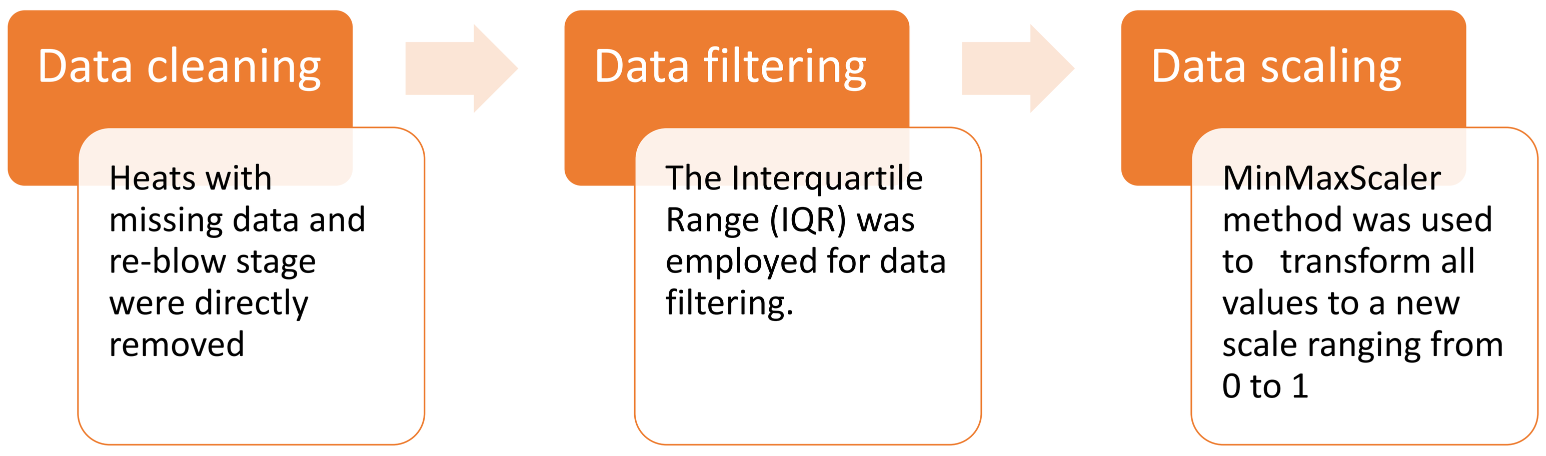

Figure 2 Data preprocessing Workflow

Ensemble learning algorithms are basically divided into two categories: boosting[5] and bagging[6]. Three Boosting algorithms: **XGboost, LightGBM, Catboost**, one bagging algorithm **random forest (RF)** and one neural network algorithm **multilayer perceptron (MLP)** were applied after data splitting. Bayesian optimization with gaussian processes was utilized for the hyperparameter tuning of all models with 5-fold cross validation.

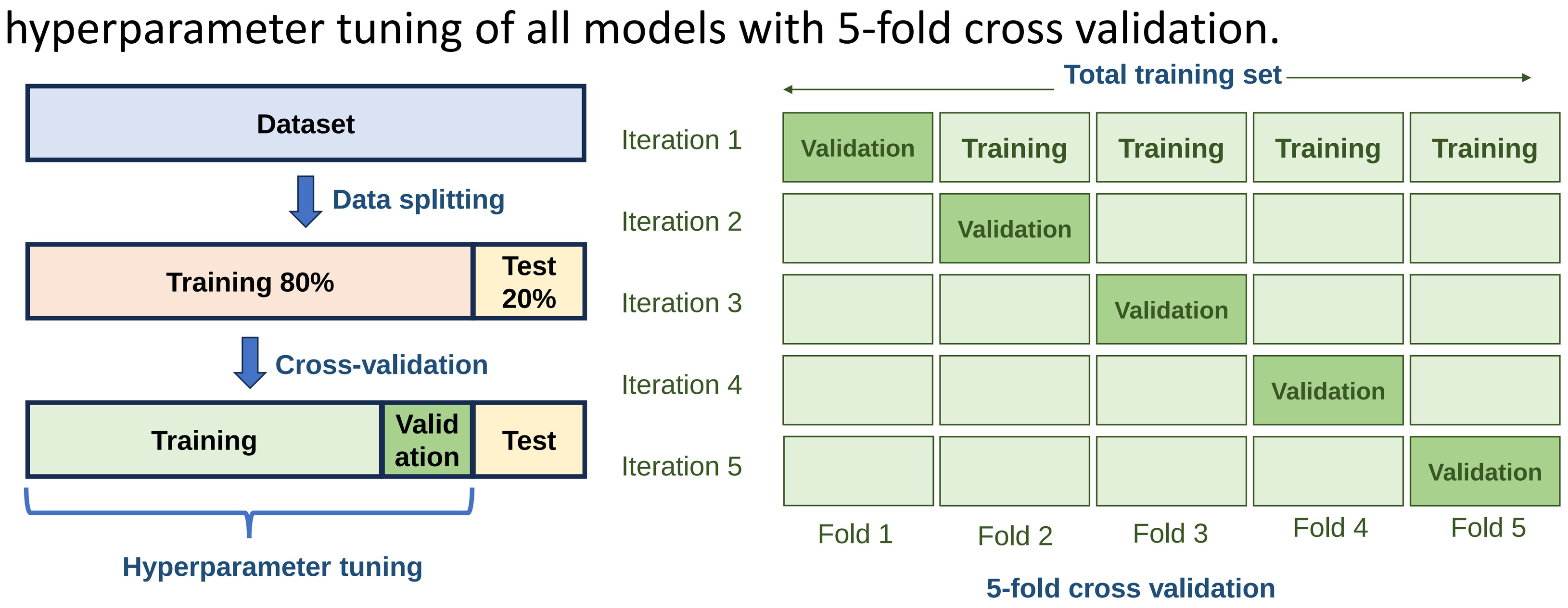

Figure 3. Conceptual Diagram of Data Splitting and 5-fold Cross-Validation Process

Results and analysis

The relationship between the main features and the end-point temperature is presented in Figure 4, which is calculated by Pearson correlation coefficient.

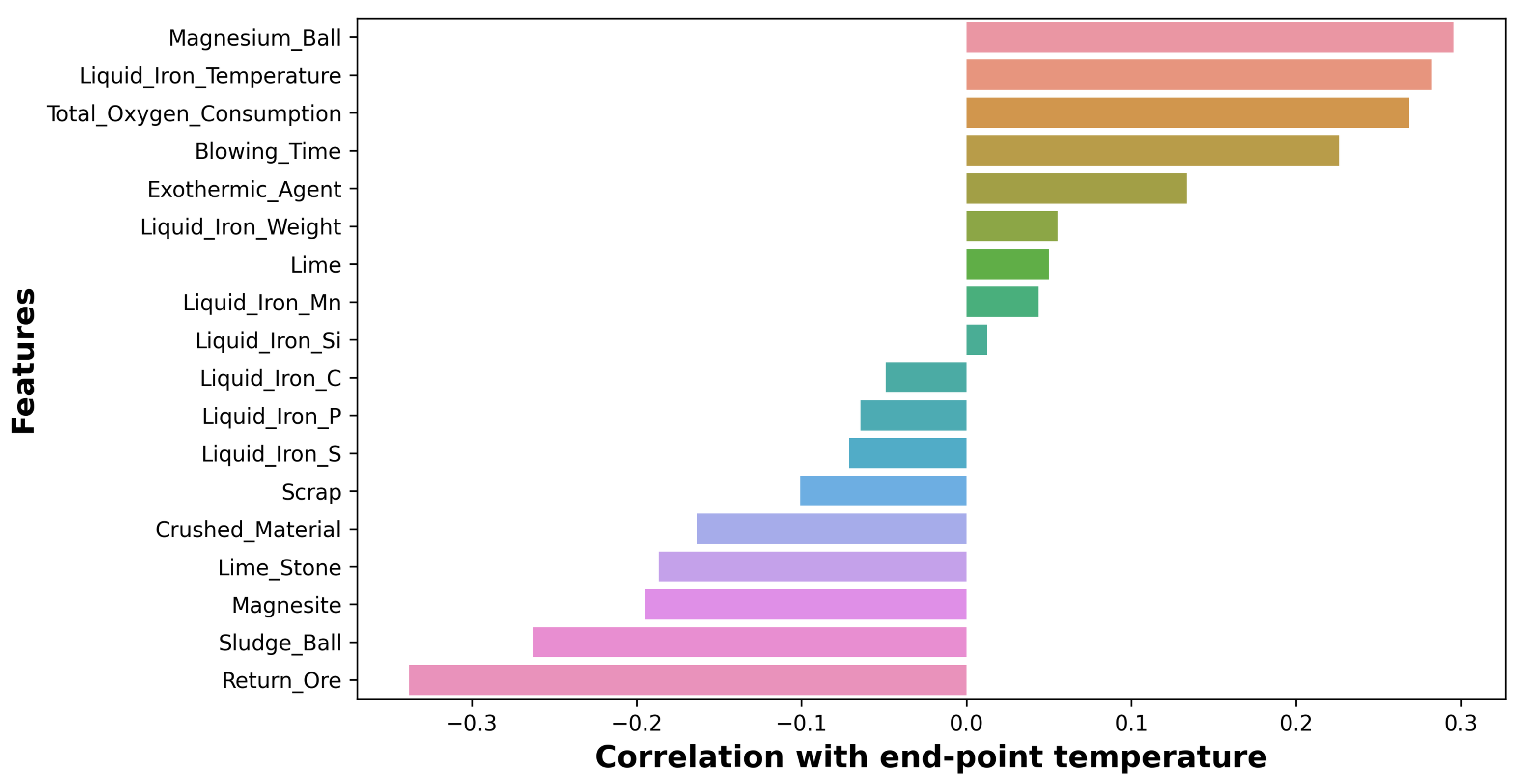

Figure 4. Correlation between main input features and end-point temperature

Results and analysis

Three kinds of metric were used to evaluate the models as follows:

Mean Squared Error: $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^{pred})^2}$

Mean Absolute Error: $MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - y_i^{pred}|$

R-squared: $R^2 = 1 - \frac{\sum(y_i - y_i^{pred})^2}{\sum(y_i - y_{mean})^2}$

Where y_i are the actual values, y_i^{pred} are the predicted values, and y_{mean} is the mean of the actual values.

Table 1 . Performance of Various models before and after Hyperparameter tuning

		Train result			Test result		
	Algorithm	RMSE	MAE	R^2	RMSE	MAE	R^2
Before Hyperparameter Tuning	XGboost	0.056	0.043	0.917	0.089	0.068	0.794
	LightGBM	0.075	0.058	0.852	0.086	0.065	0.810
	Catboost	0.059	0.053	0.876	0.085	0.065	0.815
	RF	0.036	0.027	0.967	0.091	0.070	0.785
	MLP	0.036	0.068	0.790	0.087	0.066	0.806
After Hyperparameter Tuning	XGboost	0.072	0.055	0.866	0.085	0.065	0.815
	LightGBM	0.078	0.060	0.841	0.085	0.065	0.813
	Catboost	0.067	0.051	0.882	0.084	0.064	0.818
	RF	0.035	0.027	0.968	0.091	0.070	0.785
	MLP	0.087	0.066	0.805	0.085	0.065	0.812

Overall, in terms of R^2, MAE, and RMSE on the testing data, the CatBoost algorithm proved to be the most effective, making it the preferred option for this dataset.

Figure 5 provides a clear visual comparison of the prediction results versus the actual data from various algorithms on the testing dataset. The boosting algorithm (Figures 5a, 5b, and 5c) and MLP (Figure 5e) demonstrate a more effective convergence in distribution of data points. The hit ratio, the percentage of prediction within acceptable range, of these models are close to 80% (±0.1 error range).

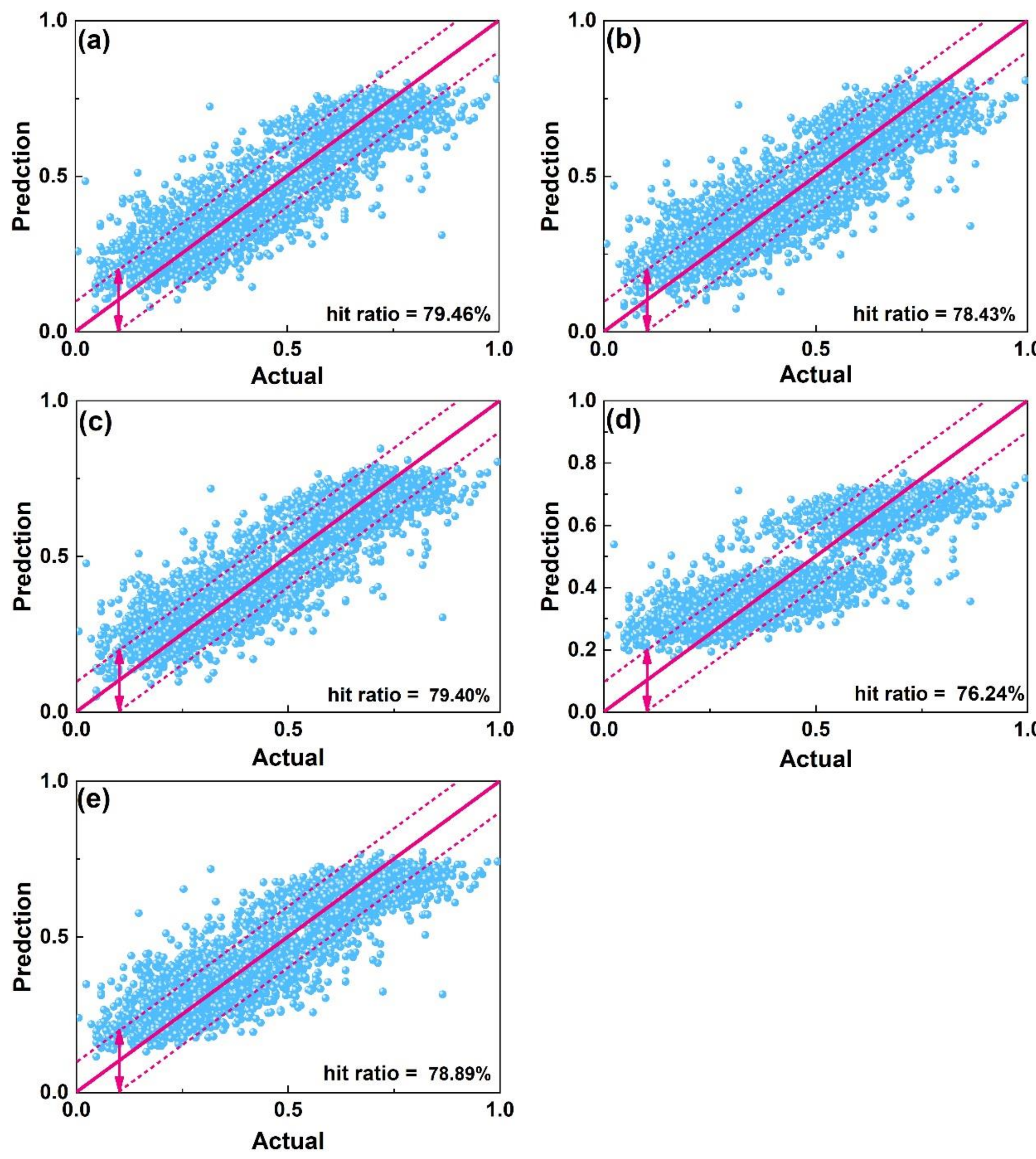

Figure 5. Comparison of Prediction values and Actual values on Testing dataset from (a)XGboost, (b)LightGBM, (c)Catboost, (d)RF and (e)MLP

Discussions and Conclusions

In this study, five algorithms were employed for predicting end-point temperature in BOF process. The dataset was subjected to extensive preprocessing, followed by the use of Bayesian optimization with Gaussian processes to optimize the models. The performance of these models was assessed using R^2, MAE, and RMSE. Overall, Bayesian-optimized CatBoost emerging as the top performer model

The complexity of the BOF process presents substantial challenges. At present, steel companies are only able to gather and utilize a limited set of features that show weak correlation with the end-point temperature. Combining on-site experience to uncover more features for modeling is extremely important in complex industrial processes.

References

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